FACTORS INFLUENCING CUSTOMER EXPERIENCE WHEN USING ANTHROPOMORPHIC GENERATIVE AI CHATBOTS: A PERSPECTIVE ON LANGUAGE STYLE AND RECOMMENDATIONS

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ABSTRACT

This study aims to determine the effect of anthropomorphic Generative AI chatbots on customer experience through the perspectives of language style and recommendations. The research method used is a quantitative approach with a survey technique. The research sample consists of students from the Office Administration Education Study Program at Surabaya State University from the 2022-2024 batch who have used Generative AI chatbots. Data analysis was conducted using Structural Equation Modeling–Generalized Structured Component Analysis (SEM-GSCA). The results of the study indicate that anthropomorphic Generative AI chatbots have a significant effect on language style and recommendations, as well as a positive effect on customer experience. In addition, language style and recommendations were also found to have a significant effect on customer experience.

Keywords: Generative AI Chatbot, Anthropomorphic, Language Style, Recommendations, Customer Experience

A. Introduction

Advances in Artificial Intelligence have driven significant transformations in customer service, particularly through the use of generative AI in the form of chatbots. This technology enables automated interactions that are more adaptive, contextual, and resemble human communication, leading to its widespread adoption by businesses, including SMEs, to enhance service efficiency and the quality of the customer experience (Mozafari et al., 2022; Rahman et al., 2024). In practice, generative AI chatbots have been deployed on various platforms such as WhatsApp, Instagram, and business websites to provide instant responses, product recommendations, and continuous customer service.

Generative AI chatbots not only function as automated response tools but also adopt anthropomorphic characteristics that mimic human behavior and communication. These characteristics utilize a more natural, flexible, and personalized conversational style, thereby enhancing user engagement and fostering a positive perception of the system (Kumar et al., 2025). Additionally, a chatbot's ability to provide relevant recommendations plays a role in influencing user decisions and shaping the overall customer experience (Zhang et al., 2024).

Within the realm of customer experience, the quality of interactions serves as a key factor in determining satisfaction and the continued use of technology. Aligning the tone of voice with user expectations has been shown to enhance emotional responses and the effectiveness of interactions, thereby improving the quality of engagement in AI-based communication (Hyun et al., 2025). Meanwhile, accurate and relevant recommendations play a crucial role in building user trust in the system, which in turn drives users' intention to adopt and use the technology sustainably (Zhang et al., 2024).

However, previous research still has limitations in examining the role of these non-technical elements. Most previous studies have focused more on technical aspects, design, and chatbot acceptance factors such as ease of use and trust, while exploration of more specific interaction aspects such as language style and recommendations regarding the customer experience remains limited (Selamat & Windasari, 2021; Kwangsawad & Jattamart, 2022). Furthermore, previous research has emphasized the importance of developing more natural interaction aspects in chatbots, thereby opening opportunities for further study on the role of anthropomorphic characters in enhancing interaction quality and user satisfaction (Cordero & Barba-guaman, 2022). This situation indicates the existence of empirical and conceptual gaps that need to be addressed. To address this gap, this study employs the Social Response Theory (SRT) approach, which posits that individuals tend to respond to technology possessing human-like characteristics as social entities (Nißen et al., 2022; Kumar et al., 2025).

Based on the above discussion, this study aims to analyze the impact of anthropomorphic generative AI chatbots on the customer experience from the perspectives of language style and recommendations. This study is expected to make a theoretical contribution to the development of research on human-technology interaction, as well as a practical contribution to SME operators in optimizing the use of AI-based chatbots to improve the quality of customer service.

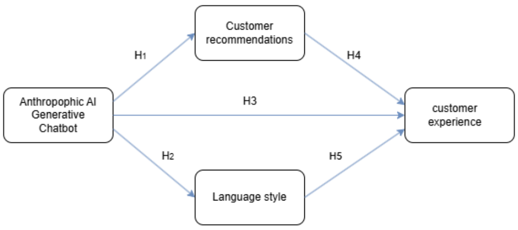

Figure 1. Model Structural

B. Method

This study employs a quantitative approach with a survey design to analyze the impact of using anthropomorphic generative AI chatbots on the customer experience from the perspectives of language style and recommendations. The study population consists of students in the Office Administration Education Program at Surabaya State University from the 2022-2024 cohorts who have used generative AI chatbots. The sample was selected using purposive sampling based on specific criteria relevant to the study's objectives. Data were collected via a Likert-scale questionnaire developed from research variable indicators, including anthropomorphic generative AI chatbots, language style, recommendations, and customer experience.

Data analysis was conducted using the Structural Equation Modeling–Generalized Structural Component Analysis (SEM-GSCA) method to test relationships among variables and evaluate the research model. The analysis stages included testing the measurement model (outer model) to assess construct validity and reliability, as well as testing the structural model (inner model) to test the proposed hypotheses. This approach was chosen because it provides robust estimates of the latent relationships within the research model.

C. Results And Discussions

This study includes current students in the Faculty of Economics and Business, Office Administration Education Program, Class of 2022–2024, who have used generative AI chatbots (Meta AI, Grok, and DeepSeek) within the past year. The main characteristics of the respondents were categorized based on the distribution of generative AI chatbot usage, cohort, gender, age, and experience in using generative AI chatbots over the past year.

Table 1. Respondent characteristics

Characteristics	Respondent	Total	%
Distribution of generative AI chatbot usage	Meta AI	118	45,4%
	Grok	40	15,4%
	DeepSeek	80	30,8%
	Other chatbots	22	8,4%
	Total	**260**	**100%**
Frequency of Chatbot Use	1–2 times	23	8,8%
	3-5 times	42	16,2%
	>5 times	195	75%
	Total	**260**	**100%**
Gender	Male	42	16,2%
	Female	218	83,8%
	Total	**260**	**100%**
Age	18–20 Years Old	144	55,4%
	21–23 Years Old	116	44,6%
	Total	260	100%
Batch	2022	88	33,8%
	2023	90	34,6%
	2024	82	31,6%
	Total	**260**	**100%**

Source: Processed Data (2026)

Measurement Model Assesment

The FIT value ranges from 0 to 1 and represents the proportion of total variance explained by all variables in the model. The higher the FIT value, the greater the proportion of variance that the research model can explain (Hwang et al., 2021). Based on the table above, the FIT value is 0.518, meaning the model explains 51.8% of the data variation. Meanwhile, the AFIT value, which is similar to FIT but accounts for the model's complexity, is 0.514, indicating that the model explains 51.4% of the variance after adjusting for its complexity. Furthermore, the FITs values also fall within the range of 0 to 1 and indicate the proportion of total variance explained by all components in the model. A FITs value of 0.371 indicates that 37.1% of the variance is explained in the structural model. Meanwhile, a FITm value of 0.548 indicates that 54.8% of the variance is successfully explained in the measurement model. According to Hwang et al. (2021), for sample sizes greater than 100, a model is considered to meet goodness-of-fit criteria if GFI > 0.93 and SRMR < 0.08. Based on the analysis results, the GFI value is 0.986 and the SRMR value is 0.052, meaning both meet the recommended model fit criteria.

Table 2. Structural model fit measures

FIT	AFIT	FITs	FITm	GFI	SRMR	OPE	OPEs	OPEm
0.518	0.514	0.371	0.548	0.986	0.052	0.485	0.636	0.454

Source: Processed Data (2026)

Based on Table 3, the Component Loadings are presented in this study. Hair et al., (2019) state that if the Component Loadings are ≥ 0.7, then the model meets the criteria. However, according to Chin, (1998), Component Loadings of ≥ 0.5–0.6 can be considered sufficient. In this study, the overall values of the Component Loadings follow Chin's statement; thus, in this study, each indicator has a value of ≥ 0.5, so the research model can be considered to meet the requirements for Component Loadings. For the anthropomorphic generative AI chatbot variable, the highest loading value is found in CGA4 (0.787), while the lowest is in CGA2 (0.536). For the recommendation variable, indicator RK3 (0.783) has the highest loading value, while RK1 (0.707) has the lowest. For the language style variables, the highest loading value is found in GH5 (0.772) and the lowest in GH1 (0.586). Meanwhile, for the customer experience variables, the PP4 indicator (0.831) shows the highest value, and PP3 (0.784) is the lowest.

Table 3. Indicator of Loading Assesment

Loadings				
	Estimate	**SE**	**95%CI(L)**	**95%CI(U)**
CGA				
CGA1	0.625	0.045	0.523	0.708
CGA2	0.536	0.052	0.445	0.638
CGA3	0.637	0.042	0.546	0.713
CGA4	0.787	0.030	0.716	0.836
CGA5	0.700	0.045	0.600	0.775
RK				
RK1	0.707	0.035	0.641	0.783
RK2	0.731	0.038	0.654	0.798
RK3	0.783	0.025	0.731	0.829
RK4	0.770	0.025	0.714	0.813
RK5	0.769	0.028	0.716	0.823
Loadings				
	Estimate	**SE**	**95%CI(L)**	**95%CI(U)**

GH				
GH1	0.586	0.054	0.461	0.673
GH2	0.735	0.035	0.679	0.795
GH3	0.743	0.034	0.661	0.796
GH4	0.769	0.028	0.711	0.815
GH5	0.772	0.025	0.724	0.810
PP				
PP1	0.803	0.026	0.736	0.846
PP2	0.821	0.022	0.776	0.861
PP3	0.784	0.027	0.727	0.828
PP4	0.831	0.021	0.787	0.870
PP5	0.829	0.019	0.785	0.864

Source: Processed Data (2026)

The measurement of construct quality was based on Hair et al., (2019), who recommended a PVE value > 0.50 to meet convergent validity, as well as Cronbach's Alpha and Rho values > 0.70 for internal consistency (Ali et al., 2021), with a dimensionality of 1 (Meneau & Moorthy, 2022). The analysis results indicate that the Anthropomorphic Generative AI Chatbot (CGA) variable has PVE and Cronbach's Alpha values below the criteria, thus not yet fully meeting validity and reliability standards. Nevertheless, this variable was retained due to its strong theoretical foundation, particularly from anthropomorphic theory which explains humans' tendency to ascribe human characteristics to technology and Social Response Theory, which posits that individuals respond to technology as if it were a social interaction with another human. These low values are likely due to the limitations of the indicators, which do not yet optimally represent the construct, as well as the respondents' subjective perceptions regarding the chatbot's human-like qualities. In the context of exploratory research, this situation is still tolerable as long as it is supported by a strong theoretical framework; however, it highlights the need to refine the indicators in future studies to ensure more accurate measurements. Meanwhile, the variables Recommendation (RK), Language Style (GH), and Customer Experience (PP) met the criteria with PVE values above 0.50 and Alpha and Rho_A above 0.70, thus being declared valid and reliable, and all variables had a dimensionality value of 1, indicating that the indicators measure the same construct.

Table 4. Construct Quality Measures (Reliability of Indicator)

	CGA	RK	GH	PP
PVE	0.438	0.566	0.524	0.662
Alpha	0.675	0.808	0.771	0.872

rho	0.793	0.866	0.845	0.907
Dimensionality	1.0	1.0	1.0	1.0

Source: Processed Data (2026)

Based on the results of the coefficient of determination (R-squared) analysis, the Anthropomorphic Generative AI Chatbot (CGA) variable yielded a value of 0.0, confirming its status as an exogenous variable that is not influenced by other variables in the research model. The Recommendation (RK) variable has a value of 0.446, indicating that 44.6% of its variance can be explained by exogenous variables, while the remaining 55.4% is influenced by other factors outside the model. Furthermore, the Writing Style (GH) variable obtained a value of 0.385, meaning 38.5% of its variance is explained by exogenous variables and 61.5% is influenced by other external variables. Meanwhile, the Customer Experience (PP) variable shows a value of 0.651, indicating that the model is able to explain 65.1% of the variance in that variable, while the remaining 34.9% is explained by factors outside the research model. Overall, these results indicate that the model possesses adequate explanatory power and meets the criteria for acceptability, thus allowing it to proceed to the structural model assessment stage.

Table 5. R Square

R squared values of components in structural model			
CGA	RK	GH	PP
0.0	0.446	0.385	0.651

Source: Processed Data (2026)

Based on the results of the effect size analysis (f^2), the relationship between Anthropomorphic Generative AI Chatbots (CGA) and Recommendations (RK) of 0.805 and with Writing Style (GH) of 0.627 falls into the category of a large effect, indicating a strong practical contribution. Meanwhile, the effect of CGA on Customer Experience (PP) of 0.056 falls into the small effect category, so its contribution is relatively limited. Nevertheless, all relationships still indicate the role of CGA in the study's structural model.

Table 6. F squared values

Eksogen → Endogen ↓	**CGA**	**RK**	**GH**	**PP**

CGA	0.000	0.805	0.627	0.056
RK	0.000	0.000	0.000	0.249
GH	0.000	0.000	0.000	0.057
PP	0.000	0.000	0.000	0.000

Source: Processed Data (2026)

Based on the results of the path coefficient analysis, all relationships between variables were found to be significant because they fell within the 95% confidence interval and did not include the value zero (Hwang et al., 2021). The Anthropomorphic Generative AI Chatbot (CGA) has a positive effect on Recommendations (RK) of 0.668 (LCI = 0.599 and UCI = 0.743), The Anthropomorphic Generative AI Chatbot (CGA) has a positive effect on Writing Style (GH) of 0.621 (LCI = 0.536; CI U = 0.743), and the Anthropomorphic Generative AI Chatbot (CGA) has a positive influence on Customer Experience (PP) of 0.229 (CI L = 0.091; CI U = 0.335), so the first, second, and third hypotheses are accepted. Additionally, Recommendations (RK) also have a positive effect on Customer Experience (PP) of 0.446 (LC = 0.307; ULC = 0.628), and Language Style (GH) has a positive effect on Customer Experience (PP) of 0.231 (LC = 0.116; CI U = 0.379), so the fourth and fifth hypotheses are also accepted. Thus, all variables in the model demonstrate a significant positive influence on customer experience.

Table 7. Path Coeffisient

	Estimate	**SE**	**95% CI(L)**	**95%CI(U)**
CGA->RK	0.668	0.035	0.599	0.743
CGA->GH	0.621	0.039	0.536	0.695
CGA->PP	0.229	0.063	0.091	0.335
RK->PP	0.446	0.085	0.307	0.628
GH->PP	0.231	0.066	0.116	0.379

Source: Processed Data (2026)

The Effect of Anthropomorphic Generative AI Chatbots on Recommendations

Anthropomorphic generative AI chatbots have a positive and significant effect on recommendations, with a coefficient of 0,668 (CI L = 0,599 dan CI U = 0,743) in the strong category. This indicates that the more anthropomorphic the chatbot's character, the higher the perceived quality of the recommendations. This effect occurs because anthropomorphic traits enhance perceptions of closeness, trust, and information relevance, making users more receptive to the provided recommendations (Youn &

Cho, 2023; Chen et al., 2025). Empirically, users prioritize speed, clarity, and relevance of information over emotional aspects; thus, the effectiveness of anthropomorphism depends on the quality of adaptive and contextual interactions. This finding is supported by Social Response Theory, which states that technology is perceived as a social entity when it is capable of providing meaningful responses (Nass and Moon, 2000). Thus, anthropomorphic generative AI chatbots have been shown to have a positive effect on recommendations, albeit a contextual one, and therefore the first hypothesis is accepted.

The Effect of Anthropomorphic Generative AI Chatbot on Language Style

Anthropomorphic generative AI chatbots have a positive and significant effect on language style, with a coefficient of 0,621 (CI L= 0,536; CI U = 0,743), classified as strong. This indicates that the higher the chatbot's anthropomorphic traits, the better its ability to adapt language style flexibly, naturally, and contextually to meet user needs. This effect occurs because anthropomorphic traits enhance perceptions of closeness and clarity in communication, making interactions easier to understand (Jiahao et al., 2025; Yang et al., 2023). Empirically, users prioritize a language style that is simple, clear, and resembles human communication over purely emotional aspects thus, the effectiveness of anthropomorphism depends on the quality of relevant and adaptive communication. This finding is supported by social response theory, which states that technology is perceived as a social entity when it is capable of providing meaningful responses. Thus, anthropomorphic generative AI chatbots have been shown to have a positive influence on language style, albeit contextually, so the second hypothesis is accepted.

The Effect of Anthropomorphic Generative AI Chatbots on Customer Experience

Anthropomorphic generative AI chatbots have a positive and significant effect on customer experience, with a coefficient of 0,229 (CI L = 0,091; CI U = 0,335), although this falls into the weak category. This indicates that the more anthropomorphic traits a chatbot possesses, the better the experience perceived by users. This effect occurs because human-like interactions can enhance perceptions of closeness, ease, and the relevance of information (Nguyen et al., 2023; Klein & Martinez, 2023). However, empirically, users prioritize speed, clarity, and the appropriateness of responses over purely emotional aspects; thus, the effectiveness of anthropomorphism depends on the quality of the interactions produced. This finding is supported by Social Response Theory, which states that technology is perceived as a social entity when it is capable of providing meaningful and contextual responses (Nass and Moon, 2000). Thus, anthropomorphic generative AI chatbots have been shown to have a positive impact on the customer experience, though this impact is contextual and not dominant, so the third hypothesis is accepted.

The Effect of Recommendations on Customer Experience

Recommendations have a positive and significant effect on customer experience, with a coefficient of 0,446 (CI L = 0,307; CI U = 0,628), which falls into the moderate-to-strong category. This indicates that the more relevant, accurate, and tailored to the user's needs the recommendations provided by the chatbot are, the more positive the user experience becomes. This effect occurs because recommendations can build trust, facilitate decision-making, and provide solutions aligned with user preferences (He et al., 2024; Dwivedi et al., 2023). Empirically, respondents value recommendations that are engaging and aligned with their interests more than mere information accuracy, while the chatbot's ability to understand context is a dominant factor in shaping the customer experience. These findings are supported by Social Response Theory, which states that recommendations are perceived as meaningful social responses when they are relevant and personalized. Thus, generative AI chatbot recommendations have been shown to positively influence the customer experience, even though they are context-dependent, and therefore the fourth hypothesis is accepted.

The Effect of Language Style on Customer Experience

Language style has a positive and significant effect on the customer experience, with a coefficient of 0.231

(CI = 0.116–0.379), although the effect falls into the weak-to-moderate category. This indicates that the clearer, more understandable, and more contextually appropriate the chatbot's writing style is, the more positive the user experience becomes. This effect occurs because a communicative language style enhances understanding and the fluency of interactions, where users prioritize clarity and relevance over emotional aspects (Cai et al., 2024; Deng, 2022). The analysis also reveals that respondents value a realistic writing style that mimics human communication, while emotional comfort alone is less dominant. These findings are supported by Social Response Theory, which states that technology is perceived as a social entity when it is capable of providing meaningful and contextual responses (Nass & Moon, 2000). Thus, the language style of generative AI chatbots has been proven to have a positive influence on the customer experience, even though this influence is contextual and not dominant; therefore, the fifth hypothesis is accepted.

E. Conclusion

This study aims to analyze the impact of anthropomorphic generative AI chatbots on the customer experience from the perspectives of language style and recommendations. Based on the results of the analysis using the SEM-GSCA approach, it can be concluded that anthropomorphic generative AI chatbots have a positive and significant influence on the language style and recommendations provided to users. This indicates that the stronger the anthropomorphic characteristics of the chatbot, the better the quality of communication produced, both in terms of the naturalness of the language and the relevance of the recommendations provided.

In addition, anthropomorphic generative AI chatbots have also been shown to have a positive impact on the customer experience. Human-like interactions can increase users' emotional engagement, thereby creating a more comfortable and enjoyable experience. A communicative, natural language style that aligns with user preferences has been shown to increase customer satisfaction, while relevant and accurate recommendations help build trust and encourage user decision-making. Thus, non-technical elements such as language style and recommendations enhanced by the chatbot's anthropomorphic character play a crucial role in creating a positive customer experience when using generative AI chatbots.

Based on these findings, it is recommended that SME operators optimize their use of generative AI chatbots by emphasizing a more human-like conversational style and providing personalized, relevant recommendations to improve the quality of customer service. Additionally, technology developers are expected to improve the chatbot's ability to understand conversational context and user preferences so that interactions become more effective and do not lead to misunderstandings. For future research, it is recommended to include additional variables such as trust, satisfaction, or perceived usefulness as mediating or moderating variables, as well as to expand the scope of the study so that the results can be generalized more broadly.

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